Lecture Notes in Intelligent Transportation and Infrastructure
Series Editor: Janusz Kacprzyk

Alberto Ochoa-Zezzatti
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Technological and Industrial Applications Associated with Intelligent Logistics

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Lecture Notes in Intelligent Transportation and Infrastructure

Series Editor

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Technical Analysis of Shipments in an Automotive Company to Forecast Sales Volumes

Fernando Anaya-Villalvazo, Alberto Ochoa-Zezzatti, Oliverio Cruz-Mejía, and Jose Diaz

Abstract This research presents an analysis of the shipments forecast of automotive sensors in three regions where such products are sold and shipped of 15,000 unique products and more than 100 million of units shipped last year. The Sensors company is one of the world's leading suppliers of sensing solutions for automotive brands with operations and business centers in 11 countries so it's very important to have a forecasting analysis based on time series as historical data is basement and estimating for 18 + months decisions. Models used in this paper are Holt-Winters, Cross Correlation and Simulation. Basically, as output of the Holt-Winters model, results show a constantly increasing forecast for the coming years when done a seasonable additive algorithm. With this model output, a prediction is performed having the forecasting till 2028 showing a stable increased of the quantity of auto sensors that are manufactured delivering to all the regions where the automotive sensors are shipped to.

Keywords Forecasting · Shipments · Holt-winters method · Predictive forecasting · Cross correlation

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1 Introduction

The Sensors company being a world leader and early innovator in mission-critical sensors designed to make the world cleaner, safer and more efficient. Mission-critical means products that are essential and difficult to do. You'll find 15,000 unique products in many automotive systems—anywhere from automotive braking systems to heavy off-road vehicles oil pressure sensors which includes, among others, the primary sensor technologies in use today are classified in three major areas of applications—powertrains, chassis and body [1]. 100 million of units are shipped per year with high revenue generated during 2018 fiscal year and now with electric vehicles rise in popularity and demand, they require sensors to monitor and optimize everything from battery systems to thermal management systems. This Sensors company is developing sensors that will enable light passenger cars, off-road vehicles and material handling equipment to operate autonomously as well as developing smart, connected sensors that enable actionable insights for commercial vehicle operators [2]. For this reason, making a forecasting analysis of sales and shipments is crucial to meet the company goals as electrification is having popularity plus big benefit to ecosystems. Then predicting the future necessity and the demand of such products, is fundamental for the company's growth as estimating the additional required capacity in the company is vital.

2 Auto Market Sensors

For the manufacturing of Electric Vehicle Technology, most company are developing flexible devices to support the requirement for more efficient electric vehicles. For this end, the processes for product assembly and calibration are machined in high volumes [2], Fig. 1. Among the requirements for these sensors are precision, efficient performance, low cost, high capacity, lightweight and compact size.

For automotive sensors, cost is a big driver in future designs. Improved signal processing will enable more information obtained from existing sensing elements and system-level software techniques will be used along with virtual sensing methods [3]. Examples of such sensors are Thermal and pressure Sensors, direct Tire Pressure sensors, battery gas sensors, and magnetic sensors, see Fig. 2 [2].

In next graph, the monthly shipment quantity is shown for sales months during 2018 and 2019 where the purpose is to forecast the shipments for following years (Fig. 3) [4].

Fig. 1 Sample of some sensors in an electric vehicle [2]

3 Methodology

Prediction or forecasting models are useful when time series are required to analyze along with other models [5]. Forecasts are important for decision-making in businesses and other organizations, like in this particular case. The predictive validity of forecasting method is assessed by comparing the accuracy of forecasts from the method with the accuracy of forecasts from currently used methods, or from simple benchmark methods such as the naive no-trend model [6]. In this paper, a time series based on Shipment Quantity of sensors built, sold, and shipped globally in the automotive market segment, is the baseline for the analysis, starting on January 2019 in a monthly basis. The regions where the items are shipped to, are Americas, Europe and Asia and for different vehicles makes. The data set consists of 12,062 rows and 10 columns. The time series is as follow where is grouped by 48 End Customer, like Audi, BMW, Volkswagen, etc. Table 1 (R generated, 2020) shows the cumulative shipments per end customer followed by the time series plot.

This data set also contains the Shipment Amount columns so doing a multivariable analysis becoming each column or variable, a temporal series where we apply the *ts*() function, the data frame cmes the *mts* class [7] and plotting it, we can see a regular trend for each column.

Fig. 2 Four buckets of the Automotive sensors manufactured and shipped [2]

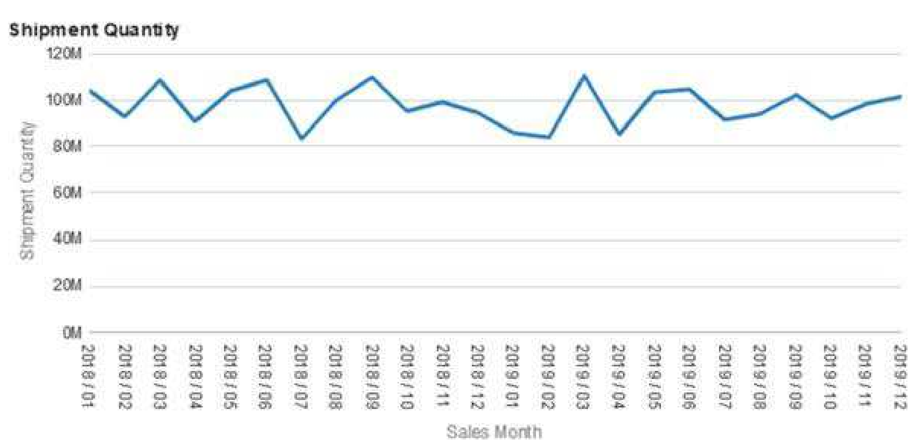

Fig. 3 Monthly shipments during 2018 and 2017 [4]

Table 1 Cumulative shipment quantity per end customer (48) (R generated, 2020)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2019	4,009,587	11,408,068	11,410,179	12,345,993	12,435,151	13,490,171	13,509,036	24,147,259	24,274,895	28,117,002	28,229,754	28,497,609
2020	28,498,614	28,533,393	28,533,884	31,983,527	46,836,165	469,667 59	47,444,004	71,581,407	72,193,891	72,819,274	72,819,850	78,455,935
2021	96,530,064	96,532,800	96,587,758	96,622,678	96,689,596	97,429,545	97,453,431	97,539,228	100,064,967	100,912,716	101,270,769	113,096,167
2022	133,473,378	134,468,575	135,240,650	135,331,033	137,868,799	138,749,419	139,228,636	140,509,179	140,934,629	145,179,441	166,415,884	169,340,542

Now the projection of the time series has gone to 3024 when exploring the full data set. There are some periods with high peaks but then comes to regular forecast, See Figs. 4 and 5 (R generated, 2020).

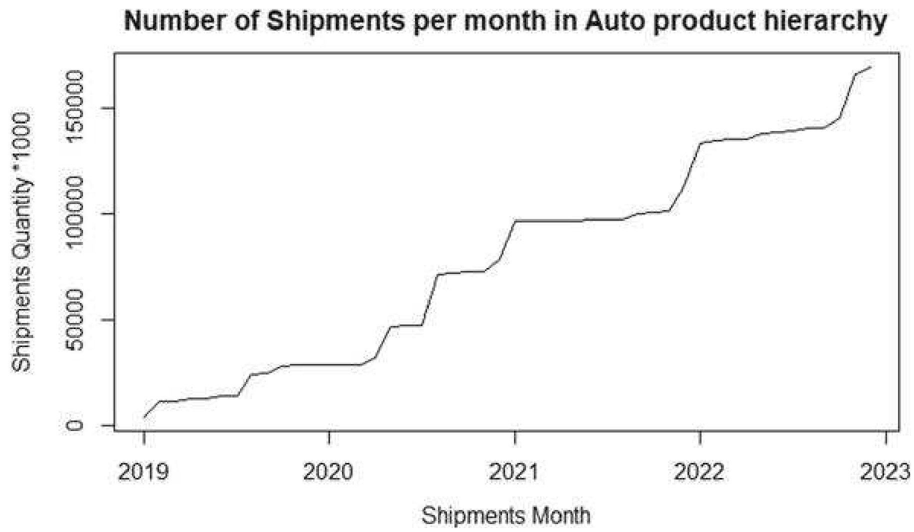

Fig. 4 Time series for shipments quantity (R generated, 2020)

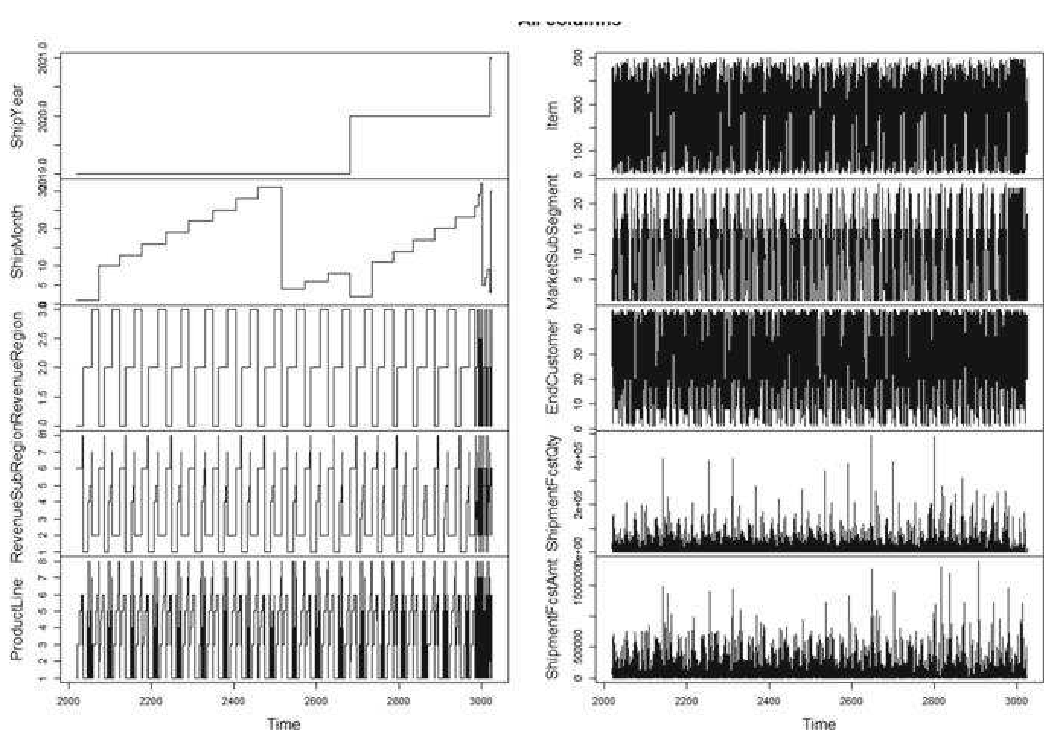

Fig. 5 Multivariable análisis (R generated, 2020)

4 Forecasting Results

For categorical forecasts accuracy is typically measured as a variation of percent correct. For quantitative forecasts, accuracy is assessed by differences between ex ante forecasts and data on what actually transpired [6]. To continue the analysis, applying autocorrelation functions on the time series for just the shipment quantity and other for all the variables, Fig. 6 shows the result (R generated, 2020).

Table 2 (R generated, 2020) shows the autocorrelation parameters in the time series for shipment quantity (Fig. 7) (R generated, 2020).

Cross correlation among the two time-series is shown in Fig. 8 (R generated, 2020) and Table 3 (R generated, 2020) include the correlation details.

Decomposing the time series, we get additional inputs, this is shown in Fig. 9. Figure 10 (R generated, 2020) shows the seasonal graph (as a seasonal plot allows the underlying seasonal pattern to be seen more clearly and is especially useful in identifying years in which pattern changes [8]) from where it can be seen that depending on the month, the shipments can vary based on the end customer and the

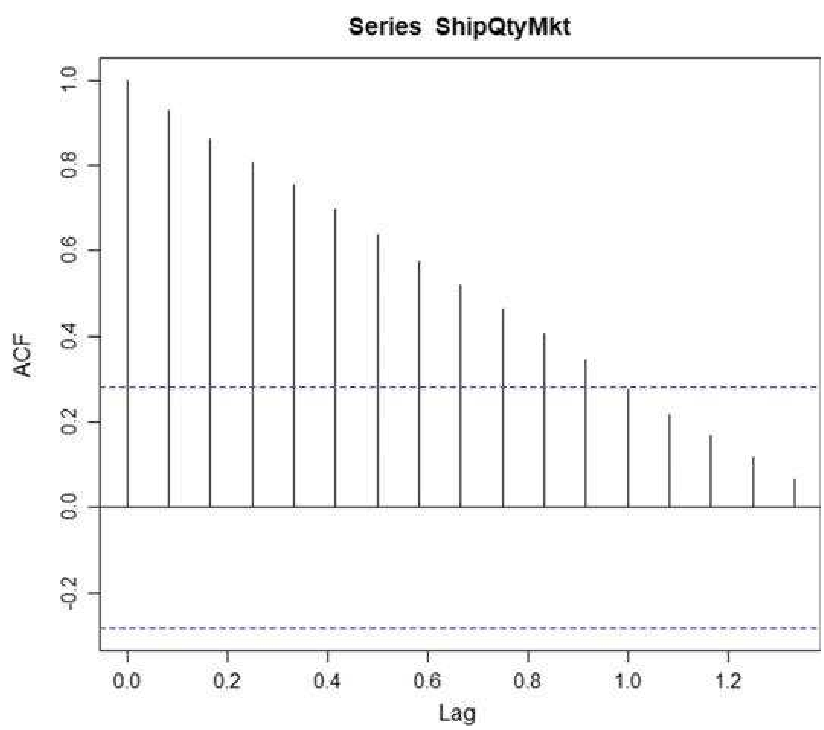

Fig. 6 Autocorrelation for Shipment Quantity (R generated, 2020)

Table 2 Autocorrelation for shipment quantity (R generated, 2020)

Autocorrelations of series 'ShipQtyMkt', by lag

0.0000	0.0833	0.1667	0.2500	0.3333	0.4167	0.5000	0.5833	0.6667	0.7500	0.8333	0.9167	1.0000	1.0833
1.000	0.929	0.861	0.807	0.754	0.697	0.637	0.576	0.521	0.463	0.405	0.342	0.276	0.218
1.1667	1.2500	1.3333											
0.168	0.117	0.066											

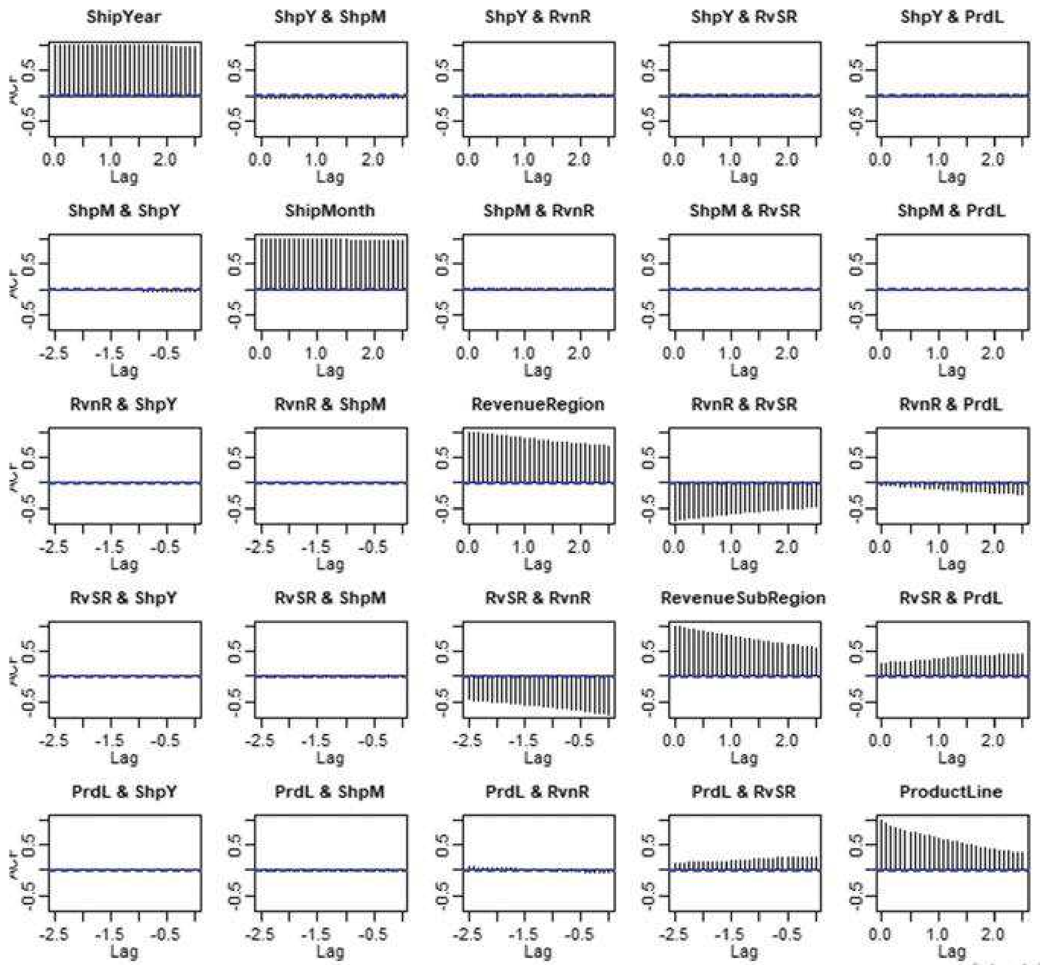

Fig. 7 Autocorrelation for all variables in the data set (R generated, 2020)

region but in general, the trend keeps showing good forecast, like the observation of the time series.

Now, using the Holt-Winters model, which simplifies both obtaining maximum likelihood estimates of all unknowns, smoothing parameters and initial conditions and the computation of point forecasts and reliable predictive intervals [9], we can observe that the additive model is the one with most adjustments as parameters are smaller so adjusting better to the observation of the time series.

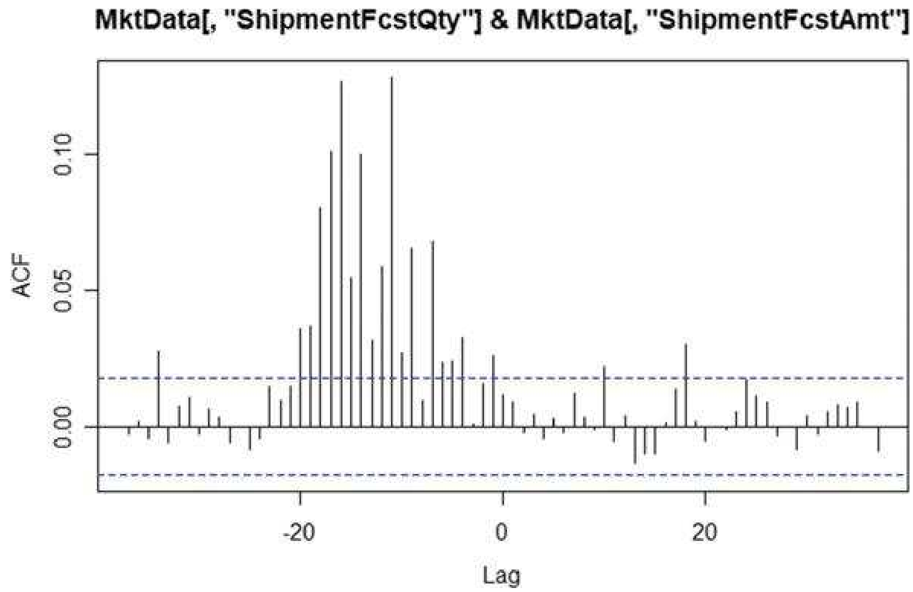

Fig. 8 Cross correlation plot (R generated, 2020)

The predictions from the model Holt—Winters Additive for the period from 2020 to 2023 with a confident interval of 95%, indicates that the growth trend continues for the following years with not many gaps but still, need to be cautious with the decisions to build enormous quantity of sensors as many factors are involved in the global market. Figure 11 (R generated, 2020) shows prediction for 2029.

Finally, we can use a data simulation or synthetic series for this case to identify the autocorrelation of the simulated shipments time series is only significant at lag 0 and with practically no variation, Fig. 12 (R generated, 2020).

Table 3 Cross correlation details (R generated, 2020)

Autocorrelations of series 'X', by lag													
−37	−36	−35	−34	−33	−32	−31	−30	−29	−28	−27	−26	−25	−24
−0.003	0.002	−0.004	0.028	−0.006	0. 008	0.011	−0.003	0.007	0.004	−0.006	0.000	−0.008	−0.004
−23	−22	−21	−20	−19	−18	−17	−16	−15	−14	−13	−12	−11	−10
0.015	0.010	0.015	0.036	0.037	0. 080	0.101	0.127	0.055	0.100	0.032	0.059	0.129	0.027
−9	−8	−7	−6	−5	−4	−3	−2	−1	0	1	2	3	4
0.065	0.010	0.068	0.024	0.024	0. 033	0.001	0.016	0.026	0.012	0.009	−0.002	0.005	−0.005
5	6	7	8	9	10	11	12	13	14	15	16	17	18
0.003	−0.002	0.012	0.003	−0.001	0. 022	−0.005	0.004	−0.014	−0.010	−0.010	0.001	0.014	0.031
19	20	21	22	23	24	25	26	27	28	29	30	31	32
0.002	−0.005	0.000	−0.001	0.005	0.017	0.011	0.009	−0.003	0.000	−0.008	0.004	−0.003	0.006
33	34	35	36	37									
0.008	0.007	0.009	0.000	−0.009									

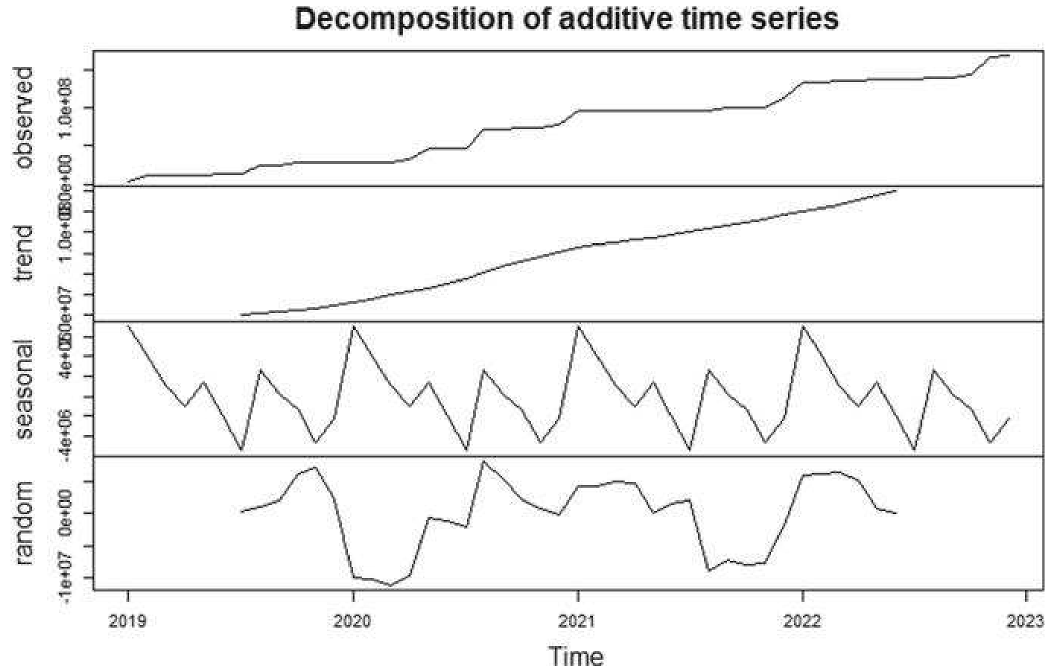

Fig. 9 Decomposition of the time series (R generated, 2020)

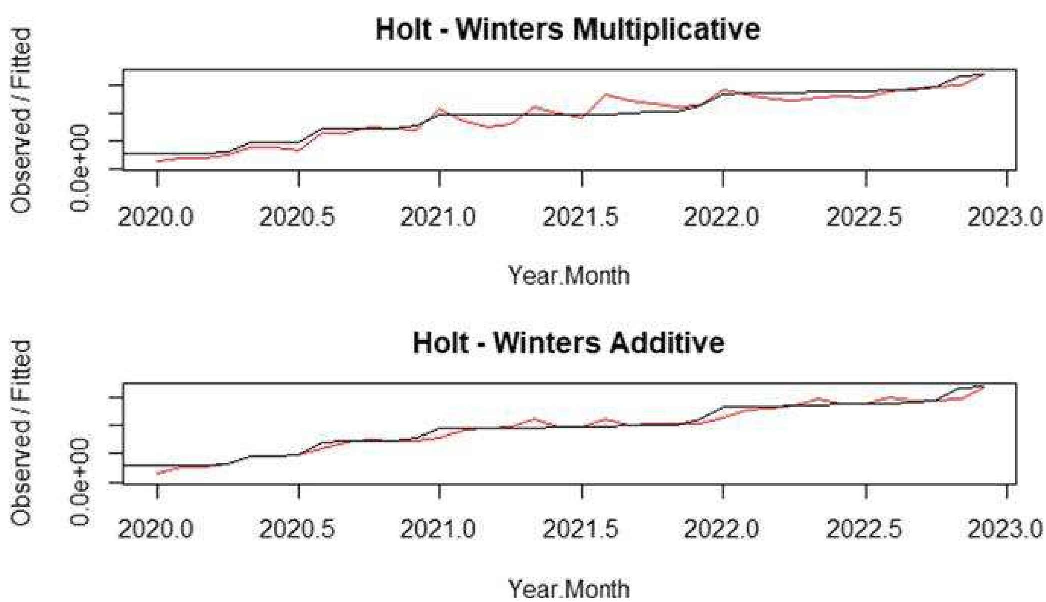

Fig. 10 Holt-Winters comparative analysis (R generated, 2020)

5 Conclusions

The predictions done by the Holt-Winters model show that the shipment quantity in the decade will continue growing based on the tendency from last years. For this reason, the Sensors company needs to consider investing in the Automotive

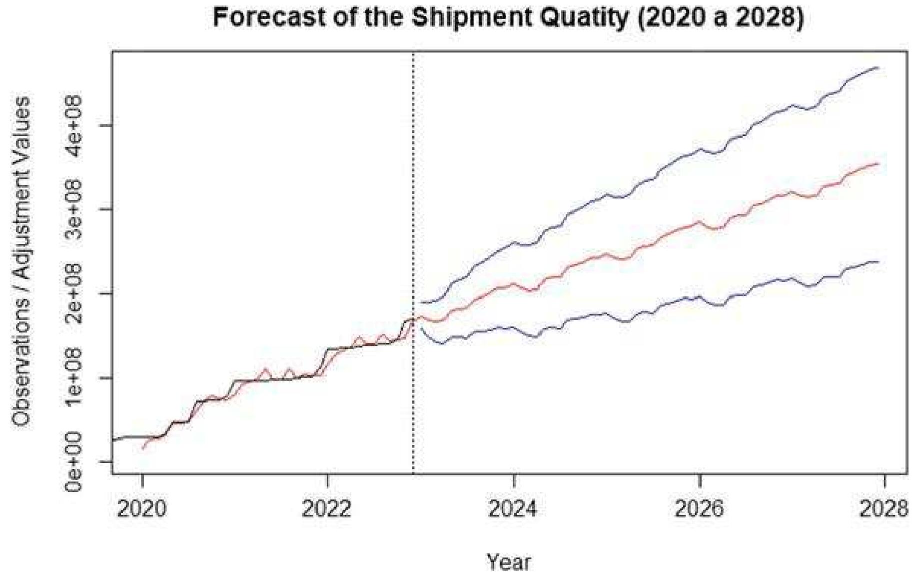

Fig. 11 Prediction of shipment quantity (R generated, 2020)

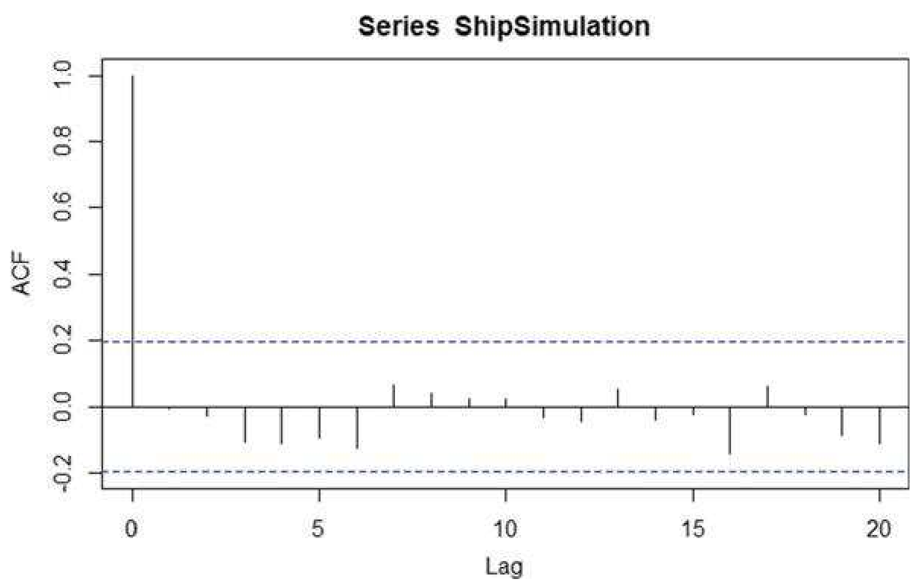

Fig. 12 Simulated autocorrelation (R generated, 2020)

market segment specially in the electrified vehicles sector. The pace of development of self-powered sensing devices is brisk, and it would have a substantial impact on automotive sensing systems [10]. But also need to be aware that this was based on a 95% confident interval, so business decisions would make the difference if not handle carefully. Current economical global factors are a consideration that need to pay attention with, so the forecasting prediction need continue under analysis and even additional models would be a good decision to run.

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